Forecasting and explaining aggregate consumer credit delinquency behaviour

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1. Introduction

The recent rise in consumer loan defaults and mortgage defaults in the US and in Europe has emphasised the significance of accurate credit risk modelling and the interdependence between the banking sector and the real economy. The recent crisis had many causes but amongst them was the increase in default rates of sub-prime mortgage loans in the US. A contributing factor was the rapid extension of loans to high risk borrowers whose ability to repay was highly dependent on the state of the macroeconomy. When house price inflation began to fall and interest rates, fuel prices and eventually unemployment increased many of these borrowers defaulted (Crouhy et al: 2008, Arner: 2009). Although this considerable rise in default rates has occurred only since 2006, there are good reasons to believe that the state of the macroeconomy has more long run effects on the proportion of borrowers that default in any one year.

It is important for lenders to be able to explain and to predict aggregate consumer delinquency over time. An increase in total consumer delinquency, *ceteris paribus* may increase the need to increase interest rate margins to compensate for increased risk and also to retain sufficient liquidity. A significant increase in delinquencies may cause lenders with low capital adequacy ratios to become insolvent causing widespread failures by contagion. The Basel II Accord (BIS 2006) allows banks to determine their own capital requirements by using their own models to forecast future probabilities of default. These probabilities must be 'through the cycle' (probabilities that do not vary with the business cycle) and a common method of obtaining these is to use a technique that involves modelling default rates in terms of macroeconomic variables (see Heitfield: 2005).

In this paper we model aggregate consumer default rates in the US over a twenty year period including the period of their recent escalation. We do this for consumer loans and for mortgages separately. We use a cointegration technique to explain long run relationships between default rates and the macroeconomy and we model changes in defaults rates in terms of deviations from the long run relationship and short-run changes in the macroeconomy. We also compare the predictive performance of these models with ARIMA models to see which methodology would give more accurate forecasts using the especially challenging task of forecasting recent events. We find evidence to support the existence of long run 'equilibrium' relationships between the level of interest rates and the level of debt outstanding on the one hand and aggregate default rates on the other, but surprisingly not between the level of house prices and the level of default rates. But we *do* find that *changes* in house prices significantly affect *changes* in default rates as do changes in disposable income, unemployment, consumer confidence, and interest rates. We also find that both forecasting methodologies gave highly accurate forecasts of default rates and were about equally accurate. Had these models been known in mid 2008 subsequent rises in default rates could have been accurately forecast. We make two contributions. We offer the first model of aggregate consumer default rates for the US using co integration techniques and so to separate long run 'equilibrium' relationships from short run dynamic relationships. Second we show a comparison of the forecasting performance between this econometric technique and ARIMA. To our knowledge this has not been done before.

The next section of the paper reviews the related literature and subsequently we explain our model. In view of the especially high interest in mortgage defaults we present our results for these sectors in separate sections. The final section concludes.

2. Related Studies

The literature suggests there are essentially three explanations as to why a borrower defaults on a loan. First, a borrower may manage his/her finances poorly due to hyperbolic discounting leading to a preference for 'irrational' immediate expenditure (Liabson et al: 2003). Second an 'ability to pay' hypothesis that a borrower will fail to pay on time when an income or expenditure shock occurs that was not expected at the time the loan was taken out. The causes of such shocks include unpredicted loss of job, marital breakdown, family bereavement, health problems, increases in interest payments on loans, and so on. Thirdly, the 'strategic default hypothesis' whereby when a loan is used to buy a real asset (for example a house), and if the capital market is perfect with no transactions costs or reputation effects, a borrower would increase his wealth if he defaulted on a loan when the value of it was greater than the value of the asset (Kau et al 1994)[1]. When considering aggregate default rates over time in the United States specifically, several explanations have been advanced. Observing the increase in credit card delinquency rates between 1994 and 1997 Gross and Souleles (2002) propose two explanations. First that the proportion of borrowers that were of high risk increased and it has been these borrowers who defaulted. Second, that borrowers 'have become more willing to default', given their risk characteristics, because the social stigma of default and associated loss of future credit supply have declined.

Previous empirical studies that have related the delinquency of credit card debt and of mortgages to macroeconomic variables have used either duration models or time series models. We start with duration models for credit cards. All three studies of which we are aware estimate *account* level duration models with macroeconomic variables as time varying co-variates. Gross and Souleles, op cit, used a panel of over 200,000 credit card borrowers. Surprisingly they found that the unemployment rate in the county of residence, the per capita income and house prices in the region were not significantly related to delinquency, and together with measures of borrower risk they could only explain a small proportion of changing delinquency rates over time. The residual was tentatively ascribed to the trend of reduced stigma. However, FCIC data suggests that if the period under consideration is extended to between 1992 and 2006, the delinquency rate on credit card debt was, if anything, trended downwards and the same was true of total consumer debt. Agarwal and Liu (2003) also use panel data for credit card holders for 1995-2001. They found the probability of a credit card holder missing three consecutive payments in a particular period, given the card holder's predicted level of risk, was increased if the lagged unemployment rate in the county or state of residence was higher, but that the change in the unemployment rate had no effect. Account balance three months earlier also positively affected the hazard rate. Bellotti and Crook (2009) estimated a proportional hazards model for a sample of credit cards issued by a UK bank between 1997 and 2001 and found that the base interest rate, real earnings, production and house prices significantly all affected the hazard rate.

Turning to account level panel models of duration for mortgage debt delinquency, Lambrecht et al (1997) used a survival model applied to 5272 borrowers in the UK to find evidence more in favour of the ability to pay argument than the strategic default hypothesis. But none of the variables they included varied over time. Deng (et al 2000) estimated a competing risks model of prepayment and default, for mortgages granted between 1976 and 1983, to investigate the extent to which the hazard rate can be explained by the strategic default hypothesis. For default to be optimal in the presence of transactions costs the put option must be in the money and trigger events like divorce or unexpected unemployment must occur. The time varying annual divorce rate and quarterly unemployment rate in the State of residence were both found to significantly affect the probability of default, as was the probability the put option was in the money. Teo (2004) used a sample of mortgage loans in Singapore to test an eclectic range of hypothesised determinants of the hazard rate. He found that whilst neither characteristics of the property bought, nor of the borrower, explained the rate, those of the mortgage and of the macroeconomy did. Teo's evidence may be interpreted as supporting both the ability to pay and strategic default hypotheses. However, Teo's study is limited by a small sample size (657 cases) and by collinearity.

Whilst account level duration models account for borrower specific characteristics, with the exception possibly of Bellotti and Crook (2009), these studies model delinquency over relatively short periods of time and they do not cover an entire business cycle. It is therefore questionable whether there is sufficient variation in the macroeconomic variables over time to accurately estimate their effect. Further, these studies have not considered the autocorrelation properties of their model residuals.

In contrast a small number of time series studies have considered data on *aggregate* default rates which, whilst they omit borrower specific characteristics, they do cover much longer periods. One of the earliest studies is by Sullivan (1987). She used data from 1975 to 1986 to find evidence in support of the ability to pay hypothesis and that the willingness of banks to lend affected default rates. But Sullivan did not consider some important factors which one would expect to be important in the explanation of delinquency rates, for example the level of interest rates, and there is evidence her empirical model may be misspecified. Grieb et al (2001) empirically modelled bank card delinquency rates over 1981 to 1999. They found these were explained by debt to income ratios, which were taken to represent capacity to pay, with no evidence supporting the ideas that delinquency was due to job market conditions, high interest rates or high credit supply. They do, however, find evidence that borrowers defaulted on credit card debt before other types of consumer debt. However, the empirical model in their study has low explanatory power and omits the possibility that an error correction mechanism may be estimated and may be more informative than the model chosen.

Two papers use error correction models to model mortgage delinquency. They use data for the UK and England and Wales respectively. Whitley et al (2004) found the proportion of mortgage loans which are at least six months in arrears is related to mortgage income gearing, unemployment, and loan to value ratio for first time buyers. However, the lack of regression diagnostics, the imputation of quarterly data from semi-annual data, and a lack of explanation of the structure of their model limits the usefulness of these results. Figuera et al (2005) use quarterly data for 1993-2001 and find that the proportion of loans that are three months overdue is related to the unemployment rate, loan to income ratio for first time buyers, unwithdrawn equity and the debt service ratio.

Clearly explanations of why some individuals default and others do not may explain aggregate default rates. For example, if there is an increase in the incidence of catastrophic net income shocks or irrational borrowing or negative equity, then one would expect an increase in aggregate default rates.

Overall the literature suggests that variations over time in aggregate delinquency rates for *unsecured* credit are due to variations in the ability of the average borrower to make repayments and to variations in the risk distribution of borrowers due to bank lending policies. For *secured* lending one can add variations in the values of real assets relative to debt outstanding on them. But apart from Bellotti and Crook (op cit), none of these papers test the forecasting ability of their models and none of the studies of US default rates give a thorough treatment of the time series properties of their data. We now turn to observed patterns in US household delinquency.

3. Patterns in Delinquency and Charge offs

Figure 1 plots delinquency and charge off rates as a percentage of debt outstanding[2] for all consumer loans and mortgages extended by all US commercial banks from 1987 until 2009. During this period the trend in charge off rates is distinctly upwards whereas until 2006 that of 30+ days delinquency is slightly downwards. This suggests that until 2006 the average period of time which was taken before a delinquent loan was charged off was shortened, especially in the period 1997-2002. The values in 2002 Q1 where the charge off rate slightly exceeds the delinquency rate is probably due to a slightly different method of calculating the two rates and possibly different methods of applying seasonal adjustment[3]. The sudden rise from 2006 is readily apparent. We construct a model to explain these patterns of aggregate delinquency in section 4.

Figure 1 Here

The delinquency rates for all consumer loans in Figure 1 mask different patterns in the rates for different types of loans. Note that consumer loans consist of credit card loans plus other consumer loans, residential real estate loans are separate. The trend for all three types of loans was downward from 1992 to 2006 (2005 for real estate loans) and rose rapidly after that. But the delinquency rate for real estate loans appears to have been little affected by the business cycle trough in late 1994 whilst the rate for consumer loans was substantially affected and credit card loans especially so. Perhaps surprisingly the consumer loans seem positively correlated in the mid 1990s. That is as real disposable income declined to 1995 Q4 and rose thereafter, default rates on consumer loans declined as well though they stopped mirroring income from about mid 1997. One possible explanation for this is that as the level of income falls so does the demand for debt and so the less credit worthy find that repayments relative to income decline and they are less likely to miss a payment or possibly to stay overdue. If there is a critical level of debt outstanding above which there are a disproportionate number of defaulters, then when income declines overdue debt will decline faster than the debt outstanding. One would expect this to apply especially to short term debt – consumer debt, and especially to credit card debt, than to debt where the borrower expects to repay over many years: residential debt. Of course to examine these possible explanations in detail requires that we examine the time series properties of the series, and construct a multivariate model, which we do in the next section.

4. The Model

We can think of the movement of the aggregate volume of debt between different states over time. We could represent this movement in a conventional transition matrix as shown in Table 1.

Table 1 Here

Where the states are: 1= No credit, 2= Up to date, 3=30+ days over due and 4= Charged off and $v_{i,j}$ is the volume of credit which moves from state *i* in period *t* to state *j* in period *t*+1. We are not assuming that $v_{j,j}$ remains constant over time. Let the period of time be one quarter. Certain values of $v_{i,j}$ must necessarily take on the value of zero. These are v_{12}, v_{13}, v_{14}, v_{41}, v_{42}, v_{43} and v_{44}.

The change in the stock of overdue debt consists of v_{23}, which is the volume which moves from being up to date to being 30+ over due, v_{31} and v_{32}, respectively the volume which moves from 30+ overdue to no credit or to up to date, and v_{34} which represents the volume which moves from 30+ to being charged off. Letting $d_t = v_{23}$, $p_t = (v_{31} + v_{32})$ and $c_t = v_{34}$ we can write:

$$s_t - s_{t-1} = (d_t - p_t) - c_t \tag{1}$$

where s_t = real volume of consumer debt which is 30+ days over due in quarter t.

We model delinquency rates in terms of the ability to pay hypothesis and, for loans on residential real estate, we include a variable to represent the strategic default hypothesis. Thus we assume that the volume of debt which is 30+ days overdue at the end of a quarter is correlated with the levels of nominal interest rates (*ri*), the volume of debt outstanding, (*ccout*), personal disposable income, (*pdi*), and expectations about future income during that period. The interest rate and level of disposable income affect the ability of a borrower to repay and so the aggregate number of borrowers who default. Expectations of higher future income may lead a borrower to wish to borrow more now and in the future and so he will not wish to risk his ability to do this by missing payments. For real estate loans we included the level of real house prices (rhp), the argument being that if house prices are low, controlling for the level of debt outstanding, the greater the proportion of borrowers for whom the value of the debt exceeds the value of the property plus transactions costs, and the greater the advantage of default, assuming the lender does not continue to pursue the debtor.

These arguments imply that the change in the stock of overdue debt, the levels of $(d_t - p_t) - c_t$, are correlated with changes in these explanatory variables. A rise interest rates or a reduction in disposable income, which at the level of a borrower could be the result of a catastrophe such as job loss or marital break-up, when aggregated across borrowers would be expected to result in an increase in aggregate volume of overdue debt.

We assume the long-run relationship between the stock of overdue debt and its determinants is linear, thus we write

$$s_t = \delta + \boldsymbol{\delta}^T \mathbf{x}_t + \varepsilon_t \tag{2}$$

Where $\mathbf{x}$ is a vector of covariates and δ and $\boldsymbol{\delta}$ are a scalar and a matrix of parameters to be estimated, respectively. ε_t represents an error term.

<u>Estimation</u>

The vector error correction representation of equation (2) is

$$\Delta s_t = \boldsymbol{\beta}^T \boldsymbol{\Delta}\mathbf{x}_{t-1} + \theta(s_{t-1} - \delta_1 - \boldsymbol{\delta}_2^T \mathbf{x}_{t-1}) + \varepsilon_t \tag{3}$$

where $\boldsymbol{\beta}$ and θ are a matrix and a scalar respectively and are to be estimated. Engle and Granger showed that if variables in the $\mathbf{x}_t$ vector, and s_t, are integrated order 1 and if a cointegrating vector exists then there is a vector error correction representation of the model, of which equation (3) is an example, where ε_t is white noise. The expression in brackets in equation (3), the error correction mechanism, represents the deviation of S_t from its long-run value of $\delta_1 + \boldsymbol{\delta}_2^T \mathbf{x}_{t-1}$. Equation 3 could be rewritten and estimated as an autoregressive distributed lag model or estimated as a vector error correction model (VEC) and in principle both sets of estimated structural parameters should be the same (Patterson 2000). Because it revealed more information overtly we chose to estimate the VEC form. We therefore tested all of the variables for the order of integration and, finding them to be I(1), except for the mortgage interest rate, we proceeded to estimate the long-run relationship using Johansen cointegrating ML procedure and then to estimate the ECM representation (Johansen (1988)).

In general, having estimated the cointegrating relationship using equation 3 with several lags, we then estimated the short-run dynamic model:

$$\begin{aligned}\Delta s_t &= \alpha + \sum_{l=1}^{4} \beta_{0l} \Delta s_{t-l} + \sum_{l=0}^{4} \beta_{1l} \Delta ri_{t-l} + \sum_{l=0}^{4} \beta_{2l} \Delta pdi_{t-l} + \sum_{l=0}^{4} \beta_{3l} \Delta ccout_{t-l} + \sum_{l=0}^{4} \beta_{4l} \Delta (optimism)_{t-l} + \\ &\sum_{l=0}^{4} \beta_{5l} \Delta (uet)_{t-l} + \sum_{l=0}^{4} \beta_{6l} \Delta (hp)_{t-1} + \\ &\theta_1 \left[s_{t-1} - \delta_1 - \delta_2 ri_{t-1} - \delta_4 ccout_{t-1} - \delta_5 (optimism)_{t-1} - \delta_6 (rhp)_{t-l} \right]\end{aligned} \tag{4}$$

Here we assumed the variables in the $\mathbf{x}_t$ vector were weakly exogenous and so included as Δx_t terms. To allow for more distant changes to affect the short-run dynamics of the model we included the first differences in the *ri, pdi, ccout, nominal house prices (hp), the unemployment rate (uet)* and optimism variables to be lagged up to four quarters and then tested down to a parsimonious form. The variables in the cointegrating vector were selected to accord with reasonable *a priori* predictions. These were that (a) it would seem implausible that at higher levels of interest rates delinquency would be lower and (b) higher consumer debt outstanding would result in higher delinquency. Disposable income is omitted from equation (4) for reasons we give in the next section.

5. Results

The data for the *volume* of overdue debt on consumer loans to commercial banks was estimated from the delinquency rates published on the FRB website. For total consumer loans the delinquency rate was multiplied by the volume of consumer loans, both seasonally unadjusted, and then was seasonally adjusted using the Stats Canada X12 routine. All of the variables were seasonally adjusted using X12 unless only seasonally adjusted values were available. The natural logs of all variables were then used. Unfortunately because of lack of data on the corresponding *amounts* of debt outstanding on credit cards, residential mortgages or other consumer loans our dependent variables for these types of loans is the delinquency *rate*. We could not find an interest rate for each separate type of loan for the entire period of our data. We were able to find data for credit card interest rates, mortgage interest rates and the mean rate for 24 month personal loans.

We first checked to see if the variables were stationary using a Phillips-Perron test. We assumed a time trend for levels but not for first differences. The results are shown in Table 2. From this it can be seen that all variables were integrated order 1, except for the mortgage rate, and so their first differences were stationary. The results of the Phillips-Perron test for mortgage interest rate varied according to the time span of data that was used. For example, it suggested that the mortgage rate was I(0) if one used the entire data series available to us (up to 2009 Q1). But if we used just up until 2008Q1 the test suggested mortgage interest rate was I(1). We chose to include mortgage interest rate in the ECM since the tests we use for a cointegrating vector would indicate no vector if the mortgage rate was not integrated order 1. The cointegrating vector and the short run dynamic models were estimated using the following data periods: volume of consumer credit: 1988 Q2 – 2008 Q1, and default rates for credit cards, other consumer loans and loans on real estate: 1992 Q2-2008 Q1. The difference in the beginning date was due to data availability. We omitted 2008Q2-2009Q1 from the estimation sample so we could use it to assess the forecasting accuracy of the model.

Table 2 Here

Because different hypotheses may explain delinquency for different types of loans: credit card loans, other loans and loans on real estate we considered delinquency behaviour for each type of loan separately.

5.1. Volume of Consumer Credit

Table 3 shows the results of the Johansen cointegration tests. For the volume of delinquent consumer debt we excluded disposable income from the long-run model because when included the Trace and Eigenvalue statistics rejected the null that there exists at least one cointegrating vector or the elasticities on income or other variables were implausible. The top panel shows both the Trace and Maximum Eigenvalue statistics for the included variables and they reject the hypothesis of at most zero cointegrating relationships but not that there is at most one. We conclude that there is only one cointegrating relationship. Table 4 column 2 shows this relationship normalised on the *volume* of delinquent debt. Since the values are all in logs (except the trend) the coefficients can be interpreted as elasticities. The relationship shows that in the long-run, *ceteris paribus*, the higher is the nominal personal loan interest rate and/or the volume of consumer debt the greater is the volume of consumer debt that is 30+ days overdue. The asymptotic t-statistics suggest both are statistically significant. The delinquency elasticity of the volume of debt in equilibrium at 2.48 is somewhat lower than for nominal interest rates at 3.42.

Columns 2 and 3 of Table 5 show the short-run dynamic equation after variables have been removed on the basis of t-statistics and *a priori* expectations and assuming all of the independent variables are weakly exogenous in explaining the volume of delinquent debt. The error correction term is highly significant and negative meaning that the greater the amount by which the volume of debt in default exceeds its long-run value in one quarter, the larger the decrease in delinquent debt in the next quarter, which is consistent with our expectations. The value implies that only 13.7% of the deviation of delinquent debt from its equilibrium value is removed in the next period.

Table 3 Here

Table 4 Here

Table 5 Here

Considering aggregate explanations, these results are consistent with credit quality explanation (increases in credit volume tends to be gained by accepting higher risk borrowers) but lend little support to the stigma hypothesis. Considering the long run relationship one would expect the positive marginal effect of the volume of consumer debt outstanding (conditional on personal loan interest rate) if the default rate was constant, but the elasticity of 2.48 indicates that the volume of delinquent would increase at a faster rate than the volume of consumer debt implying an increase in the default rate with an increase in consumer debt. The credit quality argument is also supported by the positive effect of the personal loan rate because at higher interest rates the proportion of applicants that are high risk is expected to be higher due to adverse selection. (Stiglitz and Weiss 1981) The insignificance of the trend variable is not consistent with the stigma hypothesis. The short run results add support to this interpretation. The greater the increase in consumer debt the greater is the increase in delinquent volume.

Turning to explanations at the level of the household, the results support all three hypotheses. The irrationality (irrationally borrowing debt that cannot be repaid) receives support from the magnitude of the elasticity on the level of debt outstanding and the positive sign on the change in debt in the short run equation. It is also supported by the negative sign on the lagged interest rate term. This suggests that the greater the decrease in the rate the greater the volume of delinquent debt one quarter later which is consistent with households irrationally, possibly because of hyperbolic discounting, reacting to the decline in the rate and taking on more debt than they can repay. The adverse shock hypothesis gains support form the positive sign on the personal loan interest rate: at higher levels of this rate the volume of delinquent debt is higher and from the elasticity on the volume of debt. Further support is given by the short run dynamic models where we found that a greater increase in the loan interest rate results in a greater increase in delinquency volume in the same quarter and the larger the fall in households' expected financial situation relative to their current situation the greater the increase in delinquency volume. The strategic hypothesis is consistent with the sign in the short run equation on the change in nominal house prices: the greater the fall in house prices the greater the increase in delinquent debt.

Figure 2 shows the observed and predicted volumes of overdue consumer debt. Within sample the model predicts relatively poorly in quarters 1 of 1993, the fourth quarter of 2003 and second quarter 2006, when in all three cases predicted values are much smaller than those observed and also in quarters 3 and 4 of 1993 when the predicted values are much larger than that observed. We now turn to delinquency rates.

Figure 2 Here

5.2. Delinquency Rates

We modelled the delinquency rates for two types of consumer loans separately: credit card loans and other consumer loans. These together make up total consumer loans – the variable corresponding to the volume of delinquent consumer debt in the last section. Due to data restrictions we were unable to model the volume of delinquent debt in each category. Instead the dependent variables were the volume of debt 30+ days overdue as a percentage of end-of-quarter debt outstanding. The model followed the corresponding assumptions to those above.

Credit Card Delinquency Rates

Table 3 panel 2 shows the results of the Johansen cointegration tests for the credit card delinquency rate. We excluded real disposable income because when we experimented with it we found either no cointegrating relationship or that the implied elasticities on income or on other variables were implausibly high or of an implausible sign. Both the Trace statistic and the Max Eigenvalue test suggest we can reject the null of no cointegrating vectors, but not the null that at most 1 vector exists. We conclude at there is one vector and the parameters of the vector, normalised of delinquency rate, are shown in Table 4 column 3.

Considering aggregate explanations first, the long run relationships again support the credit quality explanation. The mean credit card interest rate and the volume of total household debt outstanding are both positively related to the default rate. There is no support for the stigma hypothesis with the effect of the trend (conditional on interest rate and debt outstanding) being negative.

Looking at household level explanations, the results give support to two hypotheses but not the strategic default hypothesis. The irrational behaviour hypothesis gains support from the large and positive elasticity on household debt outstanding in the long run equation and by the negative sign on the lagged interest rate in the short run equation, the latter indicating that the greater the reduction in the interest rate the greater the increase in delinquency rate two quarters later. The adverse shock hypothesis is supported by the positive effect of interest rates in the long run and the one period lagged positive effect of a change in credit card interest rates on the increase in default rate in the following quarter. The lagged effect of increased unemployment also is consistent with the adverse shock explanation; the greater is the increase in unemployment rate in one quarter the greater the increase in delinquency two quarters later. Similarly the lagged effect of an increase in income resulting 9 months later in a decrease in delinquency rate is also consistent although the effect takes rather a long time. The argument that households miss a payment on their credit card because they have negative net equity in their house receives no support since the effect of house prices was insignificant in either of the long run or the short run models. This is entirely plausible since one would expect this hypothesis to apply only to secured lending.

The size of the adjustment coefficient on the cointegrating vector, –0.138 is similar to that for the volume of consumer debt equation

Other Consumer Debt Delinquency Rates

For other consumer loans the interest rate used was the 24 month personal loan interest rate. The cointegration tests are shown in Table 3 panel 3 and agree that there is one cointegrating relationship. Following normalisation on delinquency rate, the estimated cointegrating vector for delinquency rates on other consumer loans is given in Table 4 column 4.

Neither of the aggregate explanations gain support from the long run equations. Of the household level explanations there is support for the adverse shock hypothesis provided by the lagged positive sign on the person loan rate and the negative sign on real disposable income. The negative sign on real house prices is consistent with the strategic default hypothesis and makes sense if asset prices move consistently, so that house prices are reflecting the value of assets bought with these loans.

6. Residential Real Estate Loans

When estimating the cointegrating vector for residential loans we included a fixed rate mortgage interest rate because the vast majority of first lien primary mortgages are fixed rate. For example Buck et al, using the Survey of Consumer Finance, found that only 15% of those with a first lien primary mortgage had one with an adjustable interest rate in 2004 and only 11% in 2001 (Buck et al : 2006). We experimented with the inclusion of real personal disposable income, but when included it yielded implausibly signs or elasticities on income or other variables or few variables that were significant . We subsequently obtained two cointegrating relationships, as shown in Table 3 panel 4. We normalise the first on the delinquency rate and second on residential real estate debt and obtain the results shown in Table 4, column 5.

These results support the stigma explanation of Gross and Souleles (op cit) for delinquency; conditional on the mortgage interest rate, real house prices and sentiment, the trend in delinquency was upwards over the 1990s and 2000s. Evidence in favour of the credit quality argument is provided by the strong positive effect of the level of the mortgage rate on the level of delinquency in the long run equation and in the positive effect of the increase in the mortgage rate on the increase in delinquency rate in the short run equation. Since we use the *fixed rate* interest rate changes in this are unlikely to affect current borrowers, but it would affect new borrowers who, if offered relatively high rates and accept such rates, may subsequently find they are less able to repay than were borrowers who accepted lower rates. In short, poorer quality applicants have been accepted with banks charging higher margins to cover increased risk. The positive conditional trend effect is also consistent with a credit quality effect. Notice that our results relate to the long run over many years and not merely to the period of the recent crisis.

All three household level hypotheses are supported. The adverse shock hypothesis is supported by the effect of changes in disposable income on the changes in delinquency from the short run equations. The irrationality hypothesis is supported by the positive sign on the level of the mortgage rate and on the increase in the mortgage rate in the short run equation. Because we are using the fixed rate mortgage interest rate a change in this rate would be unlikely to affect a significant proportion of current borrowers, but it would mean that new borrowers were accepting higher rates than previous borrowers and then missing a payment. This is consistent with the irrationality hypothesis. The strategic default hypothesis is supported by the short run negative effect of lagged changes in house prices.

Table 6 Here

The adjustment coefficients suggest that just 10.6% of the deviation of the delinquency rate from its long-run path is corrected for in a quarter. Comparison with Table 4 shows this to be lower than for credit card delinquency and lower than for other consumer loans. This is consistent with homeowners trying to maintain real credit card repayments rather than real estate repayments in the short term if the short term equilibrium default rate increases to be above the long run equilibrium rate. One explanation is that the payments that are missed on a mortgage are likely to be much larger than for credit cards and so the former are less easily restored to their scheduled level from a given income. Another is that there are readily available substitutes for buying a home, for example renting, but fewer substitutes for credit cards for many types of expenditures, although this may involve losing equity.

Figure 3 shows the observed and predicted changes in default rates for residential loans. Clearly the model underestimates the size of the increase in the third quarter of 1999 and over predicts in the next quarter, and it predicts the rise in quarter 1 2005 which is one quarter early. It also under predicts in quarter 5 2002 and over predicts in quarter 3 2003. Notice that the model fits the data no less well after 2004 quarter 4, when the default rate began to rise rapidly, than before.

Figure 3 Here

7. Forecasting Performance

In this section we examine the effects of shocks to the independent variables on the volume of delinquent consumer debt and we compare the accuracy of forecasts derived from the short-run dynamic model with those given by benchmark ARIMA models. We consider only the volume of delinquency consumer debt because this is the only type of debt for which the volume of delinquent debt could be calculated.

Table 7 describes the values of the variables and indicates the shock to be applied to each in turn. The shock is typically set to roughly one standard deviation of the variable. The simulation starts from a situation where all variables are constant at their average values, the trend variable is constant at the value that makes these average values consistent with long-run equilibrium. Each variable in turn is raised by the amount of the shock and held at that higher value indefinitely. Figure 4 plots the cumulative response over 24 quarters.

Table 7 Here

All of the four independent variables are near their long-run cumulative impact within 12 quarters. Most do not move monotonically reflecting perhaps some disorientation and transitional financial adjustments that follow the shock. The impacts shown in Figure 4 shed further light on the plausibility of explanations for changes in delinquency. The impact of increased outstanding debt is consistent with the credit quality explanation of aggregate delinquency. At the level of household explanations the adverse income shock explanation is consistent with the immediate and persistent increase in delinquency volume when interest rates rise. It is also consistent with the impact of a shock to the unemployment rate which leads to no changes in delinquency volume over the first three months, perhaps whilst households are dissaving to fund repayments, but a dramatic increase in delinquency thereafter. The irrationality hypothesis is supported by the impact of a shock to optimism, which after three months results in ever increased delinquency, perhaps as households irrationally take on more debt. The strategic default hypothesis is supported by the impact of the positive shock to house prices that results in an immediate fall in delinquency volume, followed by a n increase back to the original level as households adjust to the new levels.

Figure 4 Here

The experience of credit repayment behaviour reflects the joint impact of ongoing shocks to all independent variables, and each shock response will occur before the response to previous shocks has been exhausted. Figure 2 demonstrates the model's success in coordinating these influences to track delinquency developments well and in so doing gives credibility to the predicted responses to individual variables. The comprehensiveness of the model in doing so is indicated not only by the modest magnitude of its tracking errors, but in the absence of evident pattern in these errors.

Figure 5 compares the in-sample tracking properties of the regression model with that of an ARIMA model, including also account of ex-sample forecasts by both models. Regression models are often valued for their analytical facilities in spite of inferior forecasting performance to simple models that have little explanatory content, but which manage to extrapolate well the trends and cycles in a dependent variable's behaviour. Regression models are handicapped by the need to use forecasts of the independent variables in ex-sample prediction, and thereby depend on forecast errors of the independent variables to be small or to cancel. In order to assess the extent of this handicap our model estimation excluded a holdout sample of observations for 2008 Q2 to 2009 Q1. In this four-quarter period the model will have access to actual observations only to the extent that it is fitting lagged variables observed before the holdout period. Current observations and those with short lags eventually require resort to forecast values. Table 8 indicates the ARIMA models used to forecast the independent variables. ARIMA models for the dependent variable establish a benchmark performance against which the regression model can be assessed.

Figure 5 Here

In general the ARIMA models reported in Table 8 reflect suitable parsimony with respect to numbers of estimated coefficients, but occasionally marginally insignificant parameters are adopted as well in order to achieve a suitably impressive ACF. To the extent that missed parsimony causes suboptimal forecasts of independent variables regression model forecasts will tend to appear in a poorer light compared to benchmark forecasts.

Table 8 Here

Table 9 reports ex-sample forecast performance for the regression model and its two benchmark competitors. These are m-step ahead forecasts that make no use of data observed in the ex-sample period. Wherever an ex-sample observation is needed of a forecast, relevant forecasts are used. For lagged independent variables in regression forecasts the regression forecasts are used, and for other independent variables the relevant ARIMA forecast is used.

Table 9 Here

Not surprisingly, the model's ex-sample performance has failed to achieve anything like the promise indicated by its in-sample performance. However the delinquency volume regression model roughly matches ex-sample performance achieved by the corresponding ARIMA model.

The present model that explains real estate loan delinquency rates is particularly interesting, because toxic real estate credit appears at the heart of the current global financial crisis. Figure 6 demonstrates that this model forecasts such delinquency quite well even into the holdout period, following its considerable acceleration well into that period.

Figure 6 Here

One might expect such fidelity of model performance to reflect simple appreciation of the extent that real estate credit has been radically over-extended in recent years, but that in fact is not so evident. There is a large and significant coefficient on the error correction vector for outstanding real estate debt, indicating that delinquency will be profoundly influenced by such debt being extended beyond equilibrium levels. However, Figure 7 suggests that the mechanism is perhaps not so simple. That figure does indicate debt levels persistently above equilibrium levels in recent years, but the relative magnitude of excess seems modest and stable.

Figure 7 Here

That the delinquency crisis reflects home purchase by people borrowing beyond their means can hardly be doubted, but the model suggests that the influence of income is a short-term dynamic phenomenon. There is no income variable in the cointegrating vector concerning mortgage debt outstanding, and that reflects an absence of long-run income relationship beyond what can be accounted for by proxy variables such as the trend and house prices. The more influential feature of the model is the small yet very significant coefficient on the error correction vector for real estate loan delinquency itself. Figure 8 indicates that the delinquency rate is well out of equilibrium and the model suggests that it will continue to grope upward for it for a while to come, unless there are intervening shocks in the meantime.

Figure 8 Here

8. Conclusion

We have found evidence of a long-run relationship between the volume of delinquent consumer credit and the volume of consumer debt outstanding and the interest rate on personal loans. We have also found long-run relationships between delinquency rates for credit cards, and a credit card interest rate and the level of household debt and between delinquency rates for other debt and an index of household optimism. We also found a relationship between default rates on residential real estate loans, and the mortgage rate and real house price index

These findings suggest that different explanations of delinquency are appropriate for different types of debt. For the volume of consumer debt variations in the quality of debt, but not changes in the stigma of default appear to drive delinquent volume and at the level of the household irrationality, adverse income shocks and changes in house prices are all at work. Decomposing consumer debt into debt on credit cards and that on other consumer loans we find evidence that the quality of debt and averse shocks apply but not negative equity, whereas for other consumer loans it is only strategic delinquency that applies which is plausible because credit card loans do not involve collateral whilst other loans often do. For real state loans we find that both explanations of delinquency apply as do all household level explanations.

These results are not consistent with Gross and Souleles (2002) who fund evidence of reduced stigma in the case of credit cards. Our results are only partly consistent with Grieb et al (2001); whilst we find evidence of the adverse shock hypothesis we do not find that high interest rates, higher debt and unemployment significantly affect delinquency.

We also found that the error correction model gave comparably accurate forecasts of the volume of delinquent debt as did an ARIMA model.

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Footnotes

1. More realistically, if transactions costs do exist and default does reduce the chance of a borrower gaining future loans, the option to default will not be exercised until the debt is somewhat greater than the asset value because default removes the option to default or repay in the future (Kau et al 1994). Lambrecht et al (1997) point out that for some the costs of default are higher than for others. For example those to whom access to debt is particularly important will experience a higher cost if default reduces the chance of borrowing in the future. According to the Permanent Income Hypothesis these are individuals who expect their income to rise in the future (Deaton 1992). Note also that unlike a Chapter 7 bankruptcy declaration in the United Sates, a default in some countries, for example the UK, does not prevent creditors pursuing for the debtor for repayment. In such countries this latter point removes the reason for strategic default.

2. The delinquency rate is the value of loans 30+ days overdue as a percentage of debt outstanding at the end of the quarter; the charge off rate is "are the value of loans removed from the books and charged against loss reserves, are measured net of recoveries as a percentage of average loans and annualized" (FRB).

3. The delinquency rates were seasonally adjusted by the authors using X12. The charge off figures were adjusted by the FRB.

Definitions of variables

Lnrdelsa	log of (real consumer loan debt outstanding on loans to US chartered commercial banks which is 30+ days over due, in $00 millions at year at year 2000 prices). Sources of raw data: *Charge off and delinquency rates on loans and leases at commercial banks*, Consumer loans: All. and Series G19 *Consumer Credit* debt outstanding to commercial banks. All series from FRB. Seasonally adjusted by authors using X12,.
Lnccsa	log of (consumer credit card debt to US chartered commercial banks which is 30+ days over due as a percentage of end of period corresponding debt outstanding). Sources of raw data: *Charge off and delinquency rates on loans and leases at commercial banks* , Consumer loans: Credit Cards, FRB. Seasonally adjusted by authors using X12.
Lnosa	log of (consumer non-credit card debt to US chartered commercial banks which is 30+ days over due as a percentage of end-of-period corresponding debt outstanding). Sources of raw data: *Charge off and delinquency rates on loans and leases at commercial banks*, Consumer loans: Other, FRB. Seasonally adjusted by authors using X12.
Lnrnsa	log of (single family residential mortgage debt (including home equity loans) to US chartered commercial banks which is 30+ days over due as a percentage of end-of-period corresponding debt outstanding). Sources of raw data: *Charge off and delinquency rates on loans and leases at commercial banks*, Real Estate Loans: Residential, FRB. Seasonally adjusted by authors using X12.
Lninsa	log of (nominal interest rate on 24 month personal loan). Source of raw data: *Terms of Credit, Consumer Credit Historical Data*, FRB. Seasonally adjusted by the authors using X12.
Lnrccoutsa	log of (sum of revolving and non-revolving consumer credit outstanding to commercial banks in $00 millions divided by price index personal consumption expenditure seasonally adjusted (2000=100)). Sources of raw data: FRB *Historical Consumer Credit Data, Major Types of Credit* and Bureau of Economic Analysis, *Price Indices for Personal Consumption Expenditures by Major Type of Product* Table 2.3.4. Numerator seasonally adjusted by the authors using X12.
Lnrpdisa	log of (disposable personal income (in $00 million) seasonally adjusted divided by price index personal consumption expenditure seasonally adjusted (2000=100)). Sources of raw data: *Price Indices for Personal Consumption Expenditures by Major Type of Product,* Table 2.3.4 and *Personal Income and its Disposition*, Table 2.1, Bureau of Economic Analysis.

Lnsent	log of index of relative expected change in financial situation in one year's time relative sentiment. Source: Index of Consumer Sentiment, Table 6 Expected Change in Financial Situation, *Index of Sentiment, Surveys of Consumers*, Institute for Social Research, University of Michigan. Seasonally adjusted by the authors using X12.
Lnhpisa	log of (US combined house price index seasonally adjusted). Sources of raw data: *OFHEO House price index, US Combined Index*: Office of Federal Housing Enterprise Oversight Office. OFHEO House price index seasonally adjusted by the authors using X12.
Lnrhpisa	log of (US combined house price index seasonally adjusted / price index personal consumption expenditure seasonally adjusted (2000=100)). Sources of raw data: *OFHEO House price index, US Combined Index*: Office of Federal Housing Enterprise Oversight Office*; Price Indices for Personal Consumption Expenditures by Major Type of Product*, Table 2.3.4, Bureau of Economic Analysis. OFHEO House price index seasonally adjusted by the authors using X12.
Lnrnoutsa	log of (real estate loans outstanding to Commercial Banks /price index). Source: Series bcablcr_ba.m, *Federal Reserve Board*. Numerator seasonally adjusted by the authors using X12.
Lnmisa	log of (nominal interest rate on conventional conforming 30 year fixed rate mortgages). Source: *Primary Mortgage Market Survey*, Freddie Mac. Seasonally adjusted by the authors using X12.
Lnccinsa	log of (nominal credit card interest rate). Source: Consumer Credit G19, Terms of Credit, *Federal Reserve Board*. Seasonally adjusted by the authors using X12.
Lndsrsa	Log of (debt service ratio). (Ratio of household debt payments to disposable personal income). Source: *Federal Reserve Board*. Seasonally adjusted by FRB.
Lnrtdoutsa	Log of (total credit market debt owed by household sector seasonally adjusted divided by price index personal consumption expenditure seasonally adjusted (2000=100)). Source: *Federal Reserve Board*, Flow of Funds Accounts of the United States, Outstandings, file ltab1d.prn, series FL154102005.Q and Bureau of Economic Analysis, *Price Indices for Personal Consumption Expenditures by Major Type of Product* Table 2.3.4. Numerator seasonally adjusted by the authors using X12.

All seasonal adjustments performed before logs were taken.

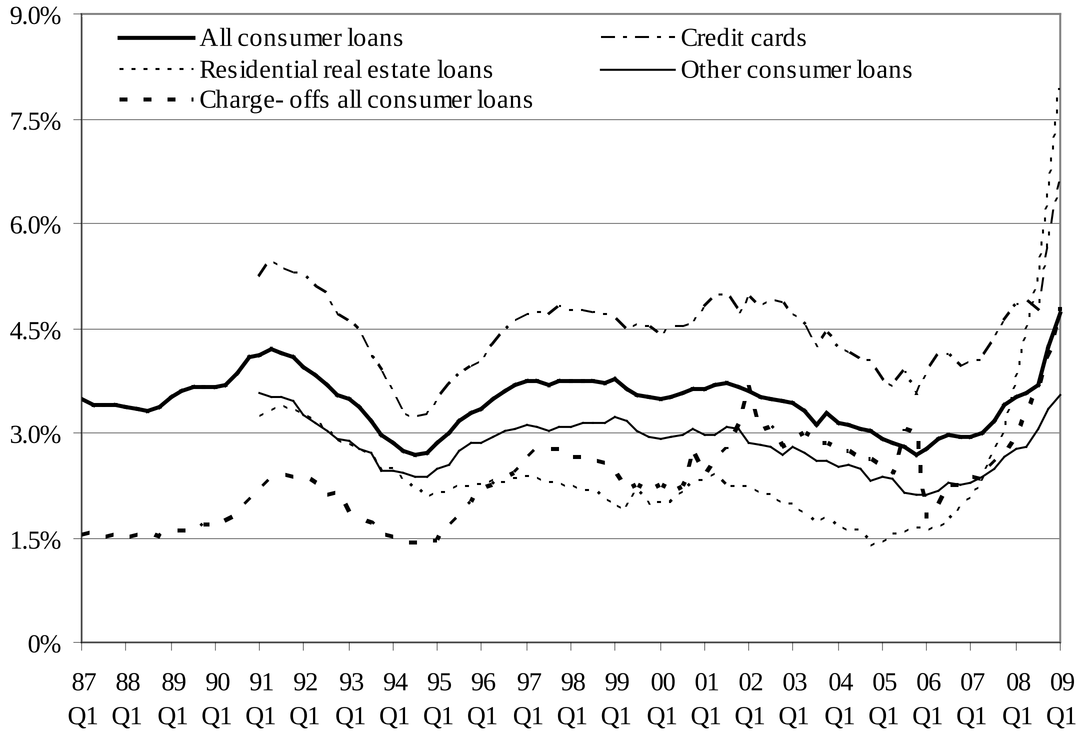

Figure 1: US Seasonally adjusted delinquency rates (30+ days overdue) and charge-off rates for different loan types

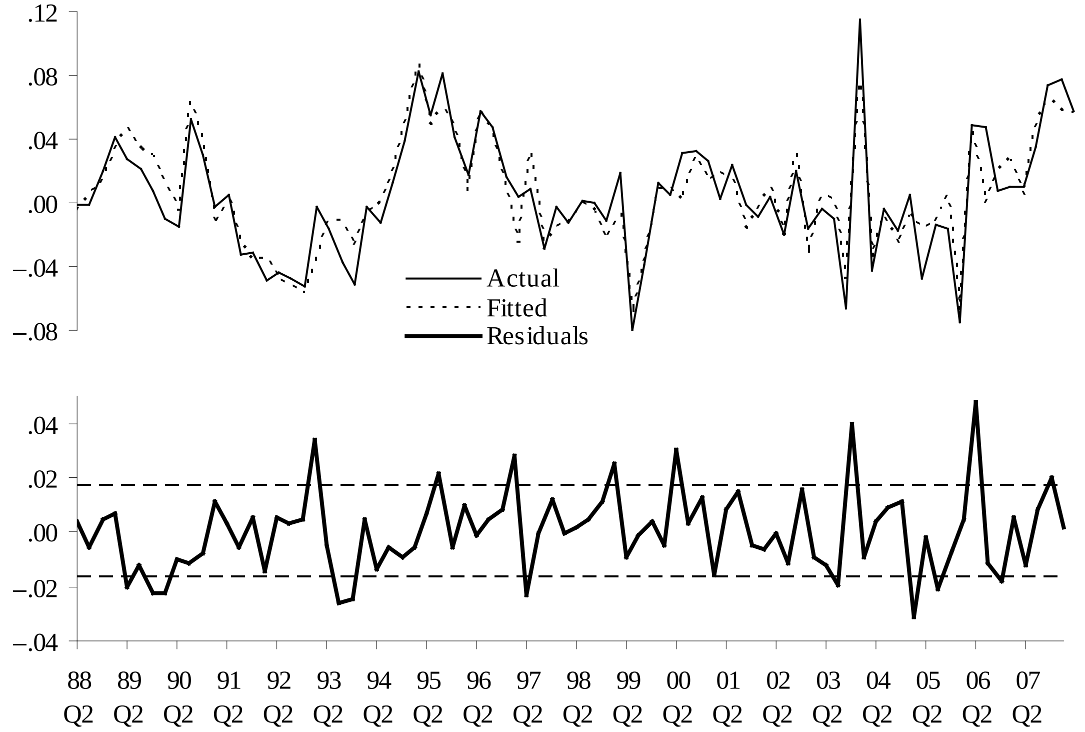

Figure 2: Changes in log volume of delinquent credit.

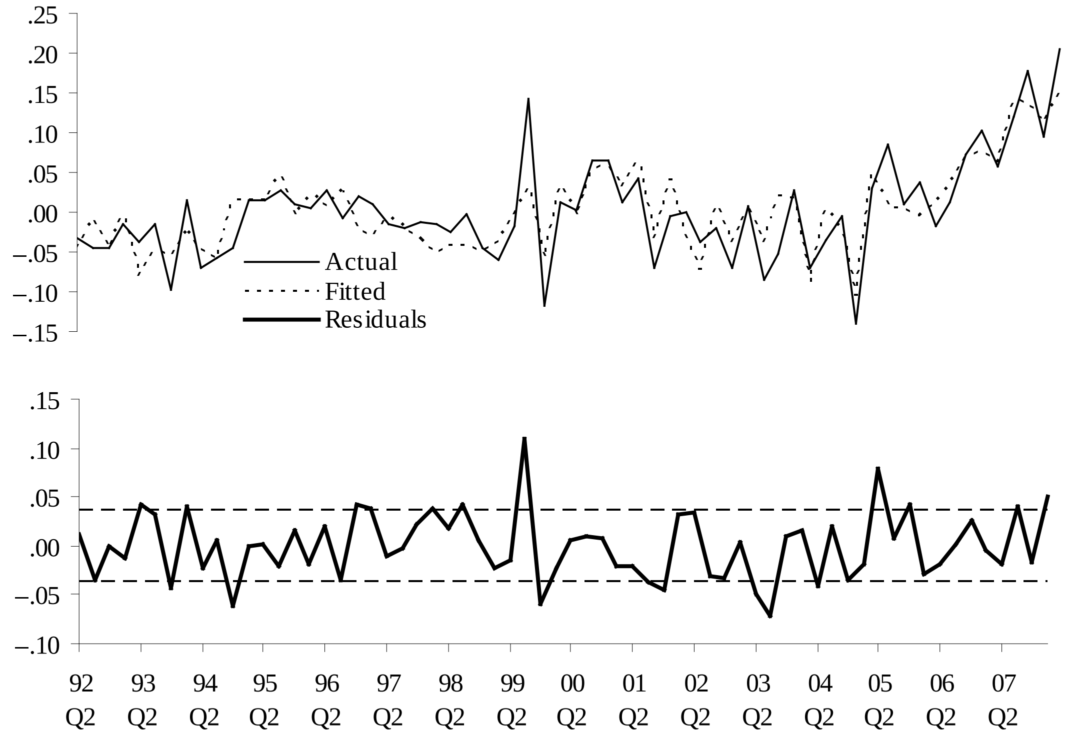

Figure 3: Changes in log default rates for residential loans.

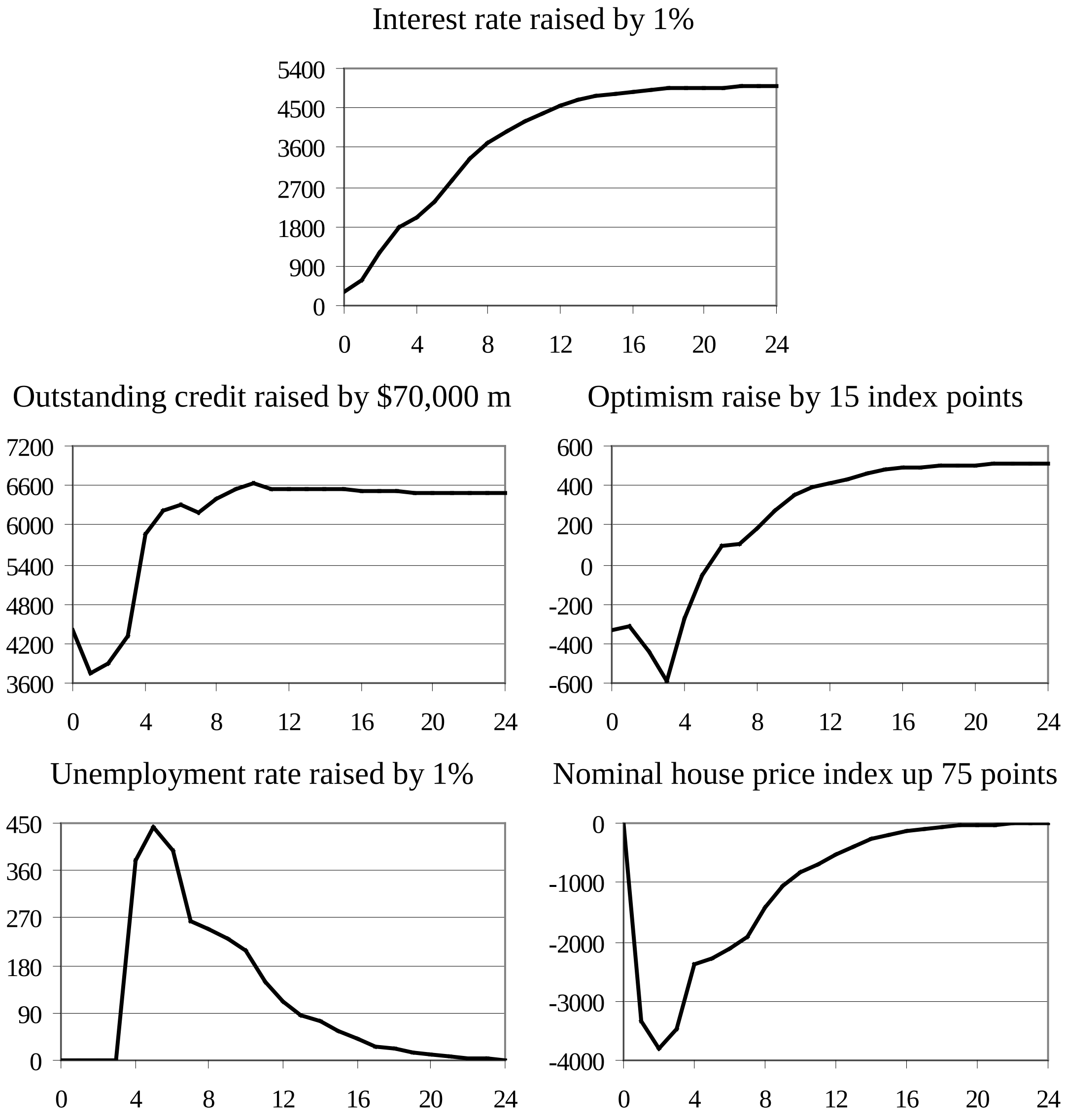

Figure 4: Cumulative impact ($ million) to volume of credit delinquency from various shocks in independent variables over 24 quarters.

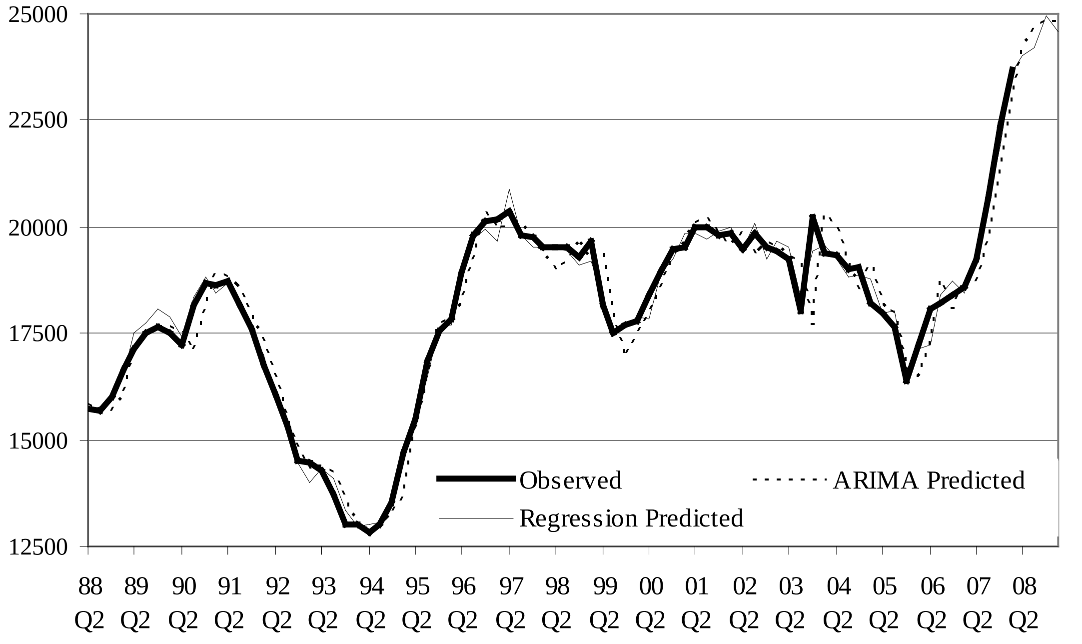

Figure 5: Tracking of alternative models for delinquency volume.

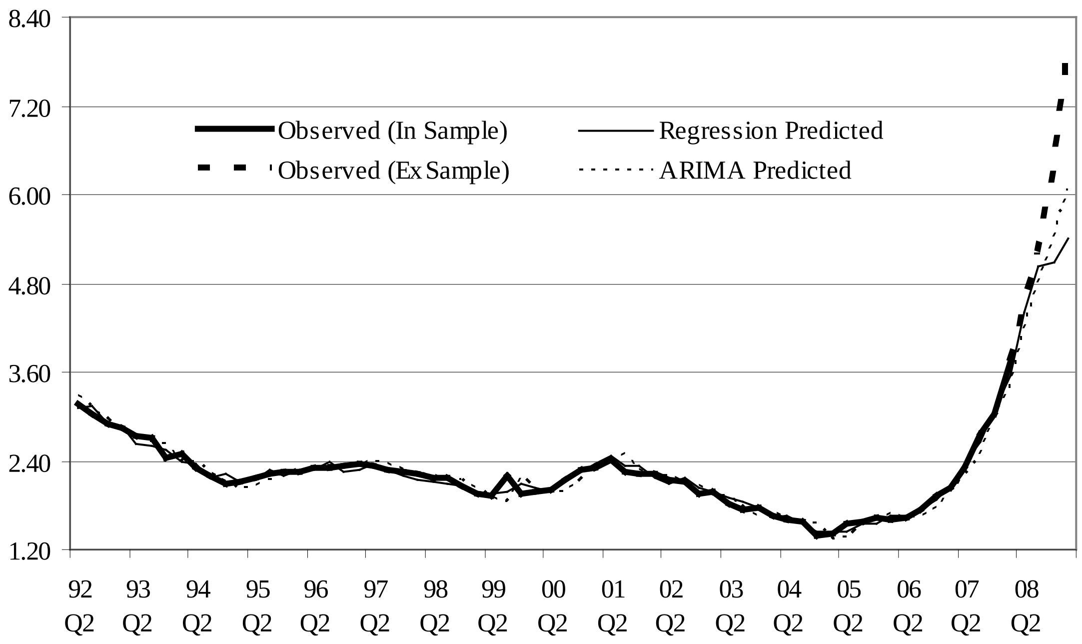

Figure 6: Tracking of alternative models for real estate loan delinquency rate.

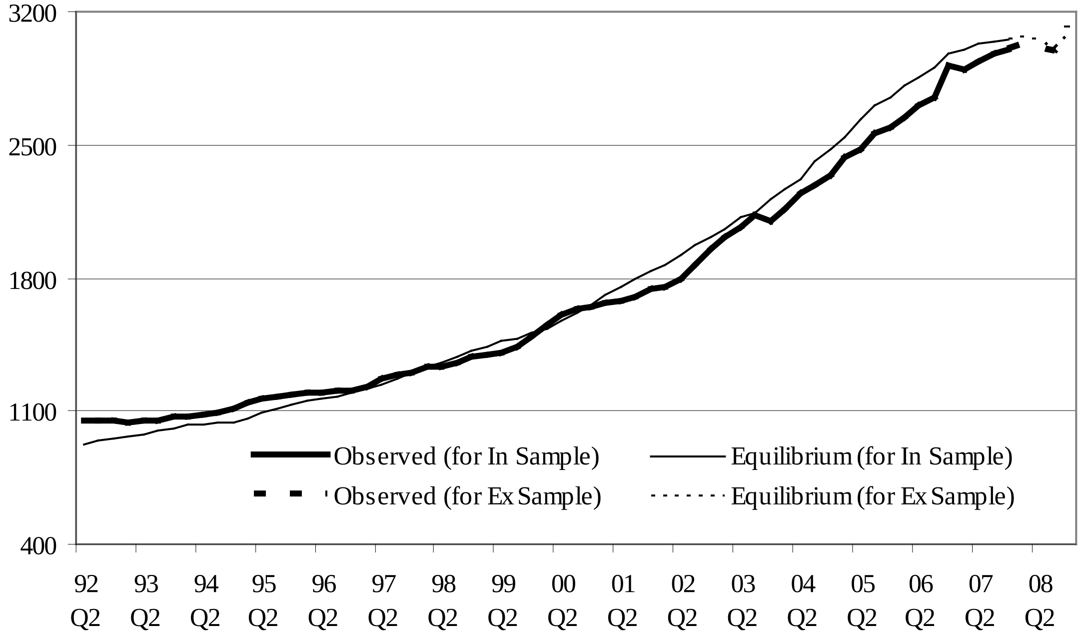

Figure 7: Observed and equilibrium real estate loans outstanding ($ million)

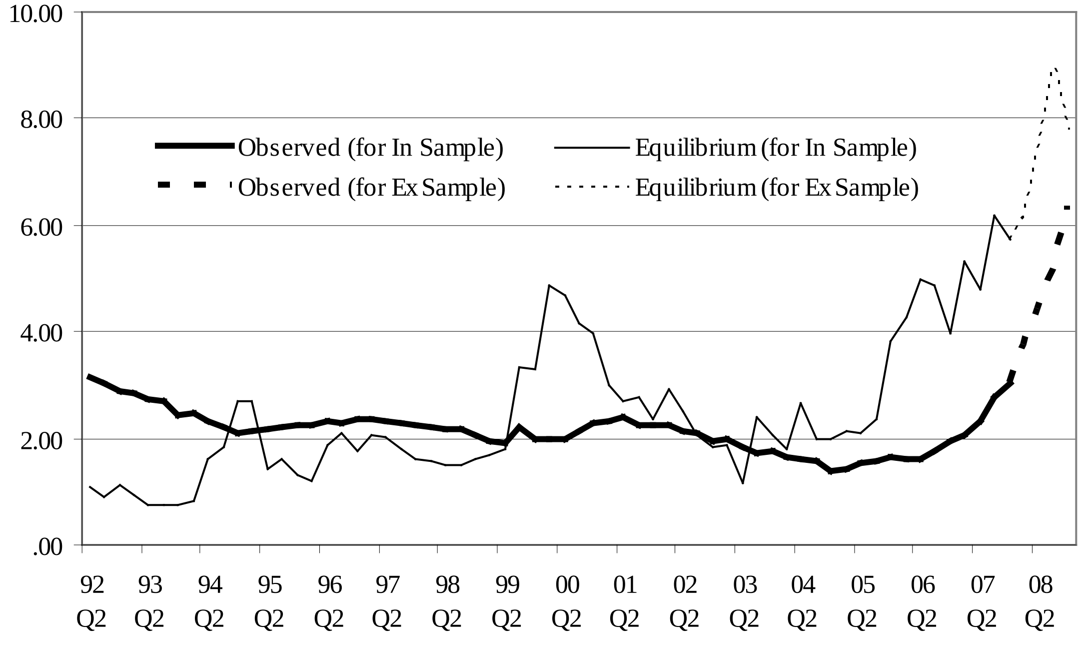

Figure 8: Observed and equilibrium real estate loan delinquency rates

Table 1: Repayments Transition Matrix

	1	2	3	4
1	v_{11}	v_{12}	v_{13}	v_{14}
2	v_{21}	v_{22}	v_{23}	v_{24}
3	v_{31}	v_{32}	v_{33}	v_{34}
4	v_{41}	v_{42}	v_{43}	v_{44}

Table 2: Phillips-Perron Unit Root Tests

	Levels (with trend)	Adjusted t-statistic	Differences (without trend)	Adjusted t-statistic
Consumer delinquency types:				
real bank consumer credit total	Lnrdelsa	-1.067	dlnrdelsa	-5.569**
bank credit card	Lnccsa	-1.143	dlnccsa	-5.763**
other bank consumer credit	Lnosa	-1.198	dlnosa	-5.154**
mortgage loan	Lnrnsa	3.462	dlnrnsa	-3.914**
Explanatory variables				
real real estate credit outstanding	Lnrnoutsa	-0.971		
real consumer credit outstanding	Lnrccoutsa	-1.979	dlnrccoutsa	-6.579**
personal loan interest rate	Lninsa	-2.782	dlninsa	-8.607**
consumer sentiment index	Lnsent	-1.958	dlnsent	-12.984**
real personal disposable income	Lnrpdisa	-2.125	dlnpdisa	-13.134**
real house price index	Lnrhpisa	1.666	dlnrhpisa	-4.250**
real real estate credit outstanding	Lnrnoutsa	-0.971	dlnrnoutsa	-7.213**
mortgage interest rate	Lnmisa	-3.578*	dlnmisa	-9.848**
real total household debt	Lnrtdoutsa	-1.466	dlnrtdoutsa	-3.494*
credit card interest rate	Lnccintsa	-2.494	dlnccintsa	-6.964**

Test period: 1987Q1 - 2009Q1 for all variables except for the consumer sentiment index for which it is 1987Q1 - 2008Q4 because Q1 2009 data was not available.

* = significant at 5% one sided test (MacKinnon)
** = significant at 1% one sided test (MacKinnon)
In all cases bandwidth 4 (Newey-West using Bartlett Kernel)

Table 3: Johansen Cointegration Tests

H_0:	Trace Statistic	5% cv	Max-Eigenvalue Statistic	5% cv
Consumer Credit				
Total real default volume (Lnrdelsa)				Ref: citestlnrdelsa1
r = 0	75.65	63.88	36.10	32.12
r ≤ 1	39.56	42.92	20.39	25.82
r ≤ 2	19.17	25.87	16.69	19.39
r ≤ 3	2.48	12.52	2.48	12.52
Lags in ECM = 4				
Credit card default rate (Lnccsa)				Ref: citestlnccsa24
r = 0	66.28	63.88	37.02	32.12
r ≤ 1	29.27	42.92	14.43	25.82
r ≤ 2	14.83	25.87	10.24	19.39
r ≤ 3	4.59	12.52	4.59	12.52
Lags in ECM = 4				
Other loans Default rate (Lnosa)				Ref: citestlnosa5
r = 0	80.52	63.88	44.21	32.12
r ≤ 1	36.31	42.92	16.02	25.82
r ≤ 2	20.29	25.87	13.83	19.39
r ≤ 3	6.46	12.52	6.46	12.52
Lags in ECM = 4				
Residential Real Estate Loans				
Default rate (Lnrnsa)				Ref: citestlnrnsa12
r = 0	119.78	88.80	41.01	38.33
r ≤ 1	78.77	63.88	35.45	32.11
r ≤ 2	43.32	42.92	22.71	25.82
r ≤ 3	20.61	25.87	10.91	19.39
r ≤ 4	9.71	12.52	9.71	12.52
Lags in ECM = 4				

The estimation samples for the models were: volume of consumer credit: 1988Q2-2008Q1; for delinquency rates for credit cards, other consumer loans and residential real estate loans: 1992Q2-2009Q1.

Table 4: Cointegrating vectors (normalized)

Dependent variable (delinquency rates or volume)		Consumer credit: Total real volume (lnrdelsa)	Consumer credit: Credit cards rate (lnccsa)	Consumer credit: Other rate (lnosa)	Residential real estate rate (lnrnsa)	Residential real estate debt (lnrnoutsa)
Estimation Period:		1988(2) - 2008(1)	1992(2) - 2008(1)	1992(2) - 2008(1)	1992(2) - 2008(1)	1992(2) - 2008(1)
Independent variables						
personal loan interest rate	lninsa	3.421179 (5.138)**		.224736 (.895)		
credit card interest rate	lnccintsa		1.052104 (2.440)**			
mortgage interest rate	lnminsa				4.440855 (4.814)**	-.058910 (-.379)
real consumer credit outstanding	lnrccoutsa	2.476919 (6.560)**				
real total household debt outstanding	Lnrtdoutsa		3.293867 (3.703)**	.326231 (.850)		
real house price index	lnrhpisa				-1.287682 (-.828)	.819381 (3.128)**
consumer sentiment index	lnsent	.250140 (.772)	4.149131 (5.550)**	2.637235 (7.538)**	-1.217450 (-.579)	.005718 (-.016)
	Trend	.000646 (.353)	-.042407 (-3.046)**	-.005393 (-.860)	.057898 (3.135)**	.012822 (4.123)**
	Constant	-32.96678	-71.12901	-17.22614	2.02118	2.298972
	Ref:	civecmlnrdelsa1	civecmlnccsa24	civecmlnosa5	civecmlnrnsa12	civecmlnrnsa12

Asymptotic t statistics in parentheses. * = significance at 5%; ** = significance at 1%

Table 5: Short run dynamic equations

Dependent Variable:	dlnrdelsa		dlnccsa		dlnosa	
Estimation Period:	1988(2) - 2008(1)		1992(2) - 2008(1)		1992(2) - 2008(1)	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Independent Variable						
Constant	.006963	1.904	.063755	4.034**	.036956	5.693**
Δ*dependent variable*						
ddepvar(-1)	.294305	3.269**	.277482	2.544*	.292584	3.222**
ddepvar(-2)			.409872	4.321**		
ddepvar(-3)	-.178716	-2.039*			.272562	2.868**
ddepvar(-4)	.191735	2.850**				
Δ*personal loan int. rate*						
dlninsa	.247647	2.061*				
dlninsa(-1)	-.318031	-2.230*				
dlninsa(-2)					.398035	2.371*
dlninsa(-4)	-.283033	-1.928				
Δ*credit card int. rate*						
dlnccisa(-1)			.995690	4.382**		
dlnccisa(-2)			-.459833	-1.847		
Δ*real cons. credit outstanding*						
dlnrccoutsa	1.769506	11.424**				
dlnrccoutsa(-1)	-.863338	-4.234**				
dlnrccoutsa(-3)	.332669	1.731				
Δ*real total debt outstanding*						
dlnrtdoutsa(-4)			-2.711368	-3.059**		
Δ*real personal disp. inc.*						
dlnrpdisa					-.960631	-2.799**
dlnrpdisa(-3)			-1.178360	-2.282*		
dlnrpdisa(-4)			-1.348418	-2.646*		
Δ*(log)optimism*						
dlnsent	-.167160	-2.520*				
dlnsent(-1)			-.580658	-3.570**		
dlnsent(-2)	-.122058	-1.753			-.195921	-1.702
dlnsent(-3)	-.152598	-2.070*			-.271455	-2.294*
dlnsent(-4)	.141314	1.981	.288269	1.979		
Δ*unemployment rate*						
dlnuets(-2)			.310217	2.519*		
dlnuets(-4)	.124044	1.981				
Δ*nominal house prices*						
dlnhpisa					-2.281425	-5.463**
dlnhpisa(-1)	-.743795	-2.887**				
error correction						
ecmlnrdelsa1(-1)	-.136846	-6.206**				
ecmlnccsa24(-1)			-.137630	-4.031**		
ecmlnosa5(-1)					-.155482	-4.988**
Adjusted R^2	.798193		.524616		.540635	
DW	2.295758		2.111985		2.094834	
Durbin's h alt.	-.104661		-.635365		-.772350	
Jarque-Bera $\chi^2(2)$	6.731451		.112595		6.360840	
RESET2 $\chi^2(1)$	.404732		1.117542		.004008	
LM het. Test $\chi^2(1)$	.053380		.614157		.191852	
F-statistic	20.528973		7.320408		10.268245	

All variable changes are in logs. * = significance at 5%; ** = significance at 1%.

Total volume of delinquent consumer debt (lnrdelsa), consumer credit outstanding (lnrccoutsa), personal disposable income (lnrpdisa), and total household debt outstanding (lnrtdoutsa) are all in real terms. House price index (lnhpisa) is in nominal values.

Table 6: Short run dynamic mortgage equation

Dependent Variable:	Log Δ in mortgage delinquency rate (dlnrnsa)		
Estimation Period:	1992(2) - 2008(1)		
Independent Variables		Coefficient	t-stat
Constant		.042408	5.360**
Δ personal loan interest rate	dlninsa(-2)	.646873	2.289*
Δ mortgage interest rate	dlnmisa	.516384	4.831**
	dlnmisa(-1)	-.432677	-4.569**
	dlnmisa(-2)	-.310225	-3.202**
	dlnmisa(-3)	-.390666	-3.665**
Δ real personal disposable income	dlnrpdisa	-2.401499	-4.128**
Δ real house price index	dlnrhpsa(-1)	-3.403896	-4.761**
Error correction	ecmlnrnsa12v1(-1)	-.106041	-7.252**
	ecmlnrnsa12v2(-1)	.400010	2.312*
Adjusted R^2		.662679	
DW		2.232973	
Jarque-Bera $\chi^2(2)$		2.76793	
RESET2 $\chi^2(1)$		1.77440	
LM het. Test$\chi^2(1)$		.002740	

All variable changes are in logs. * = significance at 5%; ** = significance at 1%.

Table 7: Summary statistics (1987 Q1 - 2008 Q1) for variables and shocks

	Delinquency ($ million) (rdelsa)	Interest Rate % (insa)	Credit (rccoutsa) ($ billion)	Sentiment Index (sent)	Unemploy-ment % (uetsa)	House Price Index (hpisa)
Minimum	12845	11.59	411750	110.37	3.93	142.11
Maximum	23689	15.70	670234	139.04	7.61	384.84
Average	17823	13.53	524853	127.23	5.46	230.25
Std. Dev.	2182	1.10	68808	6.34	.91	74.27
Shock value		1.00	70000	15.00	1.00	75.00
Delinquency impact:						
Initial		321	4417	-331	0	0
Long-run		4983	6473	507	0	0
Most extreme		4987	6621	-589	442	-3805

Table 8: ARMA models for first differences of log-transformed variables

	Benchmark Model		*Forecasting Models for Predictor Variables*									
	Delinquency		Interest Rate Δ [ln(insa)]		Credit Δ [ln(rccoutsa)]		Sentiment Δ [ln(sentsa)]		Unemployment Δ [ln(uetsa)]		House Prices Δ [ln(hpisa)]	
Performance:												
R Squared	.319977		.188680		.522937		.257891		.437084		.585216	
Std error	.031070		.017178		.011287		.027015		.029082		.005245	
Estimates:	*Coeff*	*t-stat*	*Coeff*	*t-stat*	*Coeff*	*t-stat*	*Coeff*	*t-stat*	*Coeff*	*t-stat*	*Coeff*	*t-stat*
Constant:			-.00278	-2.884**	.00497	2.317*					.01089	3.863**
AR1:	-.24360	-2.247*							.86152	8.130**		
AR2:	-.30925	-2.711**			.28798	2.504*						
AR3:					.33734	3.167**					.61883	5.849**
MA1:					-.28052	-2.388*	.24016	2.312*	.51282	3.299**	-.62447	-5.869**
MA2:			-.20841	-1.744							-.37341	-3.070**
MA5:					-.24981	-1.950						
MA11:							-.26818	-2.503*				
MA14:									.23904	2.246*		
MA18:					.36622	2.466*						
MA20:							-.31990	-2.635*				
SAR1:	.47243	2.159*			-.27847	-2.481*						
SAR2:	-.28147	-2.153*			-.25491	-2.191*						
SAR3:					-.34215	-2.809**						
SMA1:	.63859	2.946**	.31898	2.655**			.38022	3.526**	.22641	1.844		
SMA1:			.30804	2.449*					.35156	2.952**		
Box-Liung Prob:												
At lag24	.606536		.944222		.936595		.985520		.969858		.935956	
Min by lag24	.493075		.265556		.671857		.718427		.870855		.850769	

Note that constants cited above are the non-zero estimated mean value for the series, not the intercept.

Table 9: Comparison of regression forecasts with ARIMA benchmarks

Ex-sample Forecasts	**"Actual" Values**	**ARIMA Forecast**	ARIMA Errors	**Regression Forecast**	Regression Errors
2008 Q2	**24264**	**24094**	171	**23999**	266
2008 Q3	**25111**	**24675**	436	**24216**	895
2008 Q4	**29974**	**24865**	5109	**24960**	5014
2009 Q1	**33733**	**24832**	8901	**24568**	9165
Ex-sample RMSE			5137		5244
In-sample RMSE			562		268